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Design and Execution of a Location-Based Smart Complaint Management System using Priority Scheduling and Haversine Formula

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Abstract: *Three persistent problems associated with civic complaint systems in smart cities are the multiple reporting of the same incident, the absence of any framework of prioritization, and the long delay in resolving complaints without urgency indicators. The proposed model is called the Urban Priority Redressal Algorithm (UPRA), an MCDM approach utilizing the Weighted Linear Combination approach. The complaint is evaluated along three dimensions namely, Severity (S), Spatial Dimension (V), and Temporal Dimension (T). Co-located complaints are clustered into hot spots by means of spatial de-duplication using the Haversine equation with a minimum 50 meters radius around the coordinates retrieved from the Browser Geolocation API Logarithmic aggregation ensures that no single infectious issue dominates the queue and at the same time retains the importance of the signal generated by crowdsourcing. Through its emphasis on complaints whose targets have already been missed, the time element helps ensure equality. With respect to the simulation tests using a fictional municipal data set, UPRA has shown impressive results in reducing the number of unresolved complaints and in expediting the resolution of critical complaints compared to simple first-in-first-out queues. It does not require any AI infrastructure to be put in place.*

Keywords: MCDM, Smart City, Complaint Management, Haversine Formula, Weighted Linear Combination, Prescriptive Analytics, Geolocation, Urban Informatics

I. INTRODUCTION

In most Indian cities as well as other emerging urban municipalities, the complaint management process within municipalities acts only as a mechanism for collecting information, receiving complaints, giving each one a number, and passing it on to the relevant authority. However, this system does not deal with one basic question that all municipal administrators have to consider everyday, and that is, which complaint is more urgent?

Three core problems drive this research:

A. Reporting Overload of Duplicate Requests

There can be dozens or even hundreds of independent reports by individuals regarding one incident where there is a large civic issue like a collapsed roadway or broken water main pipe. This phenomenon is known as “reporting overload” because the old system treats every report as an individual ticket. In the case of a dangerous pothole near a school, sixty tickets can be submitted that will look just like a request for repairing a fence.

B. No Organised Prioritisation System

At the moment, most portals operate under the FIFO system when managing tickets for repair services. While this strategy is convenient in terms of technical performance, it can be dangerous and unfair on a social level. There is a life-threatening exposed wire behind a broken bench reported at 9:00 AM; the dangerous situation arose five minutes after reporting about the damage done to the park bench. It is impossible to tell if one ticket needs immediate attention and another is just an issue regarding aesthetic aspects of the city's territory.

C. Queuing of Low-Priority Complaints

Paradoxically, a system that is solely based on the severity of complaints ends up creating another problem, as new high priority issues keep replacing older low priority complaints that have been registered months ago. As the serious issues continue to arrive, an issue regarding the broken street lights might remain unattended for six months, and in the long run, this will demotivate citizens from making any effort to participate in the process, ultimately breeding distrust in the system.The above-mentioned three problems - duplication, inadequate prioritization, and queuing - are responsible for the inefficiency of current complaint management systems, not because of the lack of information, but rather the lack of intelligence behind the information.

The aim of this research is to transform the passively stored complaints repository to an intelligent system that will help municipal administrators to take decisions. The specific aims include:

- To develop a well-defined mathematical formulation for prioritization of citizen complaints considering time criticality, geographic importance, and severity of the complaint.
- To implement an efficient deduplication algorithm that takes care of redundancy in the database by merging duplicates to generate a single hot spot entry.
- To design a temporal escalation scheme such that there will be no backlog of complaints even for lower-level criticality complaints.
- To evaluate the proposed UPRA model on synthetic datasets of municipal complaints of tier-2 cities of India against the baseline models (FIFO, Severity Only).
- To demonstrate that the system is viable in terms of implementation without relying on cloud-based artificial intelligence services, specialised hardware, or machine learning algorithms, thereby ensuring feasibility for municipalities operating with limited budgets.
- To provide a prescriptive analytics framework to objectively generate an automatically scored ranking of work orders, thus eliminating the need for human judgement in the prioritisation process.

II. LITERATURE REVIEW

A. Multi-Criteria Decision Making within Urban Systems

In the academic literature, MCDM approaches have been recognized for application within urban planning and management practices. Investment decision-making processes relating to infrastructure development within areas such as transport, water supplies, and energy systems tend to be ranked based on Saaty's Analytic Hierarchy Process (AHP) approach [1]. In a similar fashion, Hwang and Yoon's TOPSIS technique [2] has been applied to urban resource allocation problems.

Malczewski [3] identified WLC as the most widely used MCDM model in GIS applications based on his extensive review of the literature on GIS-assisted MCDM methodologies. Given that the technique allows decision-makers to scrutinize and verify every single value, which is integral to public sector governance, our model adopts WLC as the foundation of its mathematical formulation rather than AHP or TOPSIS.

This area of literature also suffers from an obvious void. In almost all instances where MCDM has been applied to urban systems, it has involved infrastructure planning. This involves infrequent decision-making by experts over long periods of time (days or weeks), rather than frequent real-time decision-making based on citizens' complaints. Through its modification of WLC for high frequency and real-time triage, UPRA meets this gap.

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B. E-Governance and Complaint Management Systems

The most detailed study about the complaint management process in e-governance of cities in India has been presented by Kumar, Singh, and Mehta [4]. Due to the fact that the processing process was still done manually in an unstructured manner, the authors found that despite higher complaint submissions through digitization, there were no improvements in terms of resolution time and quality.

Improvement wise, Zhang and Patel [5] developed category routing that allows complaint allocation to departments based on the nature of the complaint. Other improvements like duplication avoidance across the organization and prioritization by departments did not take center stage, but there was a reduction in misdirected complaints.

Spatial complaints collection and citizens' engagement on a mass scale have been demonstrated as feasible by business entities such as SeeClickFix and FixMyStreet. Nevertheless, as the literature suggests, the reasonings for prioritizing by these applications remain undisclosed; moreover, according to unofficial assessments, the number of votes and freshness are the main determinants in ranking, which are not sufficient for assessing technical and spatial importance of the problem.

C. Spatial Deduplication and Proximity-Based Clustering

Problems of removing duplicates based on geographic connections have generally only been explored in the contexts of public health monitoring and crime data collection. Where, while Kulldorff's spatial scan statistic [7] provided a framework for locating geographic clusters of events relating to health, Mohler et al.'s [6] work demonstrated the usefulness of geographic clustering for predictive policing.

There is very little academic literature concerning spatial deduplication in relation to civic complaints. The choice made by this paper in favor of employing Haversine buffer thresholds for comparison is deliberate due to the fact that it is possible to integrate it into a web backend using ordinary computer processing, which eliminates the need for specialized geographic information systems and takes O(1) computational time.

D. Temporal Prioritization and Queue Fairness

Queue hunger has been explored at great lengths by operations research literature, whereby low priority requests keep getting bumped by high priority requests arriving into the system. In their analysis of time-weighted priority queues in the context of service systems, Kleinbaum and Klein [8] established the importance of the effects of aging as vital elements in providing service to all the members in the queue. It is clear from the above statement that our Temporal Escalation factor (T) ensures that the complainant eventually moves to the top of the queue despite the priority level assigned to him.

For the case of public grievances, the unique definition of T as a normalized time ratio relative to the SLA objective is novel and acts as an intermediate for connecting the municipality information systems to queuing theory.

III. METHODOLOGY

A. Research Methodology in General

The research adopts a design science approach, where a real-life problem is found, and artefacts are developed as solutions to that problem, which includes designing and specifying the artefact, implementation in a functioning system, and evaluation through a simulated yet realistic data set relative to the benchmark cases. As UPRA is a deterministic model which can be audited, argued about, and fine-tuned by the municipal officials without any requirement of knowledge of AI, the approach adopted is deliberately machine learning free.

B. System Design

The architecture of the SCMS is developed using readily available open source tools, and it consists of three layers, namely, the Presentation layer, which serves as both the dashboard for the administration and a responsive citizen interface, made up of HTML5, CSS3, and JavaScript programming languages. Spatial Deduplication using Haversine

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Distance module and UPRA Scoring Engine reside in the Logic Layer, implemented in Node.js with Express framework. The Data Layer consists of the complaint information with geographic attributes stored in a relational database, such as MySQL or PostgreSQL.

Users are able to make a complaint using a single REST API (/complaint). Once the complaint is received, the Logic Layer initiates a two-step pipeline process: computation or update of UPRA score followed by the spatial deduplication process, which checks for duplication of hotspots based on the complaint data

C. The UPRA Scoring Model

The UPRA algorithm uses a Weighted Linear Combination of three normalized criteria to calculate a scalar priority score P for every complaint:

$$P = (w_s \cdot S) + (w_v \cdot V) + (w_t \cdot T)$$

The three criteria are: Temporal Escalation (T), which gauges how past due the complaint is in relation to its service-level agreement target; Spatial Impact (V), which captures both the geographic significance of the complaint location and the number of co-located reports; and Severity (S), which rates the intrinsic technical hazard of the issue category on a 1–10 scale. The default weights, which prioritize safety over social volume and time sensitivity, are $w_s = 0.5$, $w_v = 0.3$, and $w_t = 0.2$.

D. Deduplication in Space

Spatial deduplication computes the great circle distance between the geographical coordinates of the complaint received and all active complaints having the same category based on the Haversine formula. Rather than creating a fresh database entry, the new complaint is appended to any current complaint falling within a 50-meter threshold from each other, thereby raising their report number N. A 50-meter threshold was selected as this is about one part of an urban block while accounting for inaccuracies in GPS readings from mobile browsers ranging from 5 to 40 meters.

E. Evaluation Methodology

A synthetic dataset consisting of 1,200 complaint records was generated because a publicly available labelled dataset with GPS coordinates of complaints in a tier-2 Indian city did not exist. The geographical coordinates were obtained based on the Gaussian mixture model fit on the ward map of a typical tier-2 Indian city. The geographical cluster formation, time of report, and categorisation have been calibrated based on empirical values by Kumar et al. [4]. Three performance measures were employed to evaluate the relative performance of the UPRA algorithm versus that of FIFO and Severity-Only benchmarks, namely the Duplicate Record Rate, SLA Violation Percentage at Day 30, and MTR.

IV. SYSTEM DESIGN

The SCMS architecture is designed based on three-tiered web application. Presentation Layer includes the administration panel and citizen interface. The UPRA scoring algorithm and spatial de-duplication algorithm operate in the Logic Layer which is coded using Node.js programming language. The Data Layer contains complaint information with geographic attributes stored in the relational database system.

GPS coordinates of the complaining citizen are collected in real-time when the report is made via Browser Geolocation API. Two parallel processing procedures are initiated immediately by the Logic Layer – the Spatial De-Duplication Process and UPRA Scoring Algorithm. The outcome of this procedure determines whether to update the hot spot information or register a new complaint record.

Table I: Summary of System Components

Layer	Technology	Responsibility
Presentation	HTML5 / JS / CSS3	Citizen portal, Admin dashboard, Geolocation capture

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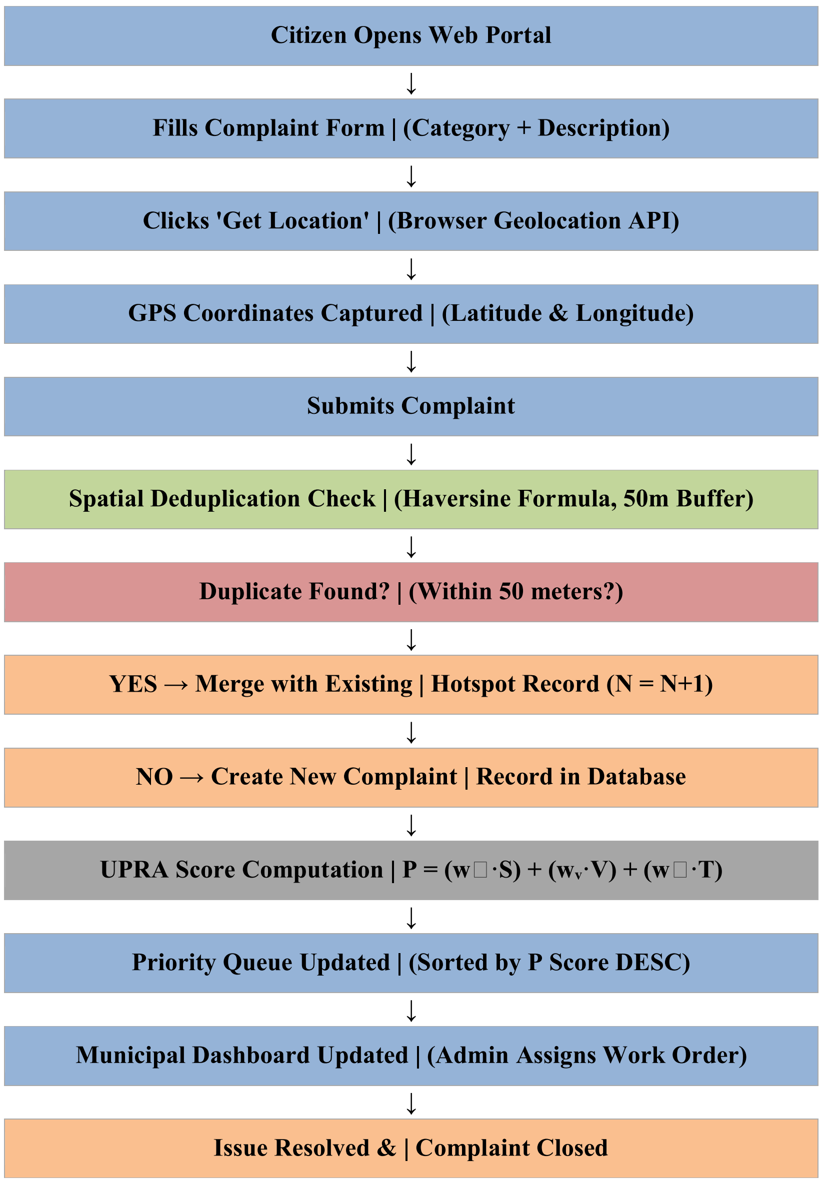
Logic	Express / Node.js	UPRA scoring, Haversine deduplication, routing
Data	MySQL / PostgreSQL	Complaint storage, hotspot records, audit log

Figure 1: System Data Flow — SCMS End-to-End Process



V. THE UPRA MATHEMATICAL MODEL AND SPATIAL DEDUPLICATION ENGINE

A. Formal Definition

Let $C = \{c_1, c_2, ..., c_□\}$ represent the set of n active complaints in the system at any given instant t. The UPRA model uses the Weighted Linear Combination to calculate a scalar priority score $P(c_i)$ for every complaint c_i,

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$$P = (w_s \cdot S) + (w_v \cdot V) + (w_t \cdot T)$$

where w_s, w_v, and w_t [0,1] are the corresponding weights of the normalized scalar criteria S, V, and T, subject to the constraint $w_s + w_v + w_t = 1$. $W_s = 0.5$, $w_v = 0.3$, and $w_t = 0.2$ are the empirically validated default weights used in this work, indicating the importance of public safety over social volume and temporal aspects.

B. Severity Index (S)

Regardless of time or place, S measures the inherent technical risk of the reported issue category. Based on organized expert elicitation in accordance with urban safety standards, issues are categorized into four Risk Tiers:

Table II: Classification of Severity Risk Tiers

Tier	S Value	Category	Examples
1 — Critical	10	Life-threatening	Open manhole, exposed live wire, gas leak
2 — High	7	Major infrastructure	Burst water main, blocked arterial road
3 — Medium	5	Health / Hygiene	Garbage accumulation, stagnant water
4 — Low	2	General maintenance	Broken streetlight, dead tree limb

C. Spatial Impact Factor (V)

The formula for V captures the social component of the complaint, taking into consideration the place and number of individuals who have separately raised this issue. Unlike the variable S, the value of V is updated dynamically based on the result of each merge operation, as follows:

$$V = L + \alpha \cdot \log(N)$$

where N represents the sum of all reports for that particular hot spot, α is a scaling factor that can be varied ($\alpha = 2$ by default) which dictates the importance of reporters increasing the priority factor, and L[1,10] is the base location weight which takes into account the civil importance of the location of the incident report. The use of the logarithm helps ensure that often-reported issues receive their due importance without mathematically overshadowing all other entries in the queue.

D. Temporal Escalation Factor (T)

T is a normalized indicator of how past due a complaint is in relation to its category's Service Level Agreement (SLA) target:

$$T = (t\_current - t\_report) / t\_target$$

Any overdue problem classified as low severity will always be moved above any recent problem classified as medium severity when $T>1.0$ since this means the problem has violated the service level agreement, and the temporal factor is significantly influencing P. This is a requirement for a fair queue.

A. The Haversine Formula

The Haversine formula is used to calculate the great-circle distance between two GPS coordinate pairs (φ_1, λ_1) and (φ_2, λ_2):

$$\mathbf{a = \sin^2((\varphi_2-\varphi_1)/2)\cos(\varphi_1)\cdot\cos(\varphi_2)\cdot\sin^2((\lambda_2-\lambda_1)/2)\ d = 2R \cdot \arcsin(\sqrt{a}),\quad R = 6{,}371\ km}$$

In urban civic applications, the formula is precise enough up to sub-kilometer distances and fast enough (O(1) per pair). The query used for deduplication is suitable for real-time processing without using spatial indexes since the maximum number of distance calculations is bounded by O(C), where C is the number of complaints in a city.

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B. Buffer Threshold and GPS Accuracy

The following two considerations informed the selection of the 50-meter buffer. One, the buffer size corresponds to the granularity of civic issues since a city block segment constitutes the typical spatial resolution of an issue. Two, the average GPS accuracy of mobile browsers lies between 5 to 15 meters under optimal conditions and 15 to 40 meters under less-than-optimal urban canyon environments [9]. This degree of inaccuracy can be compensated for by a 50-meter buffer that is even less than the distance between issues on the same street.

VI. EXPERIMENTAL EVALUATION

A. Dataset and Simulation Setup

The reason for developing a synthetic dataset of 1,200 observations is that there is not any such type of GPS tagged urban complaint data set that can be accessed freely for the purposes of this study. The coordinates of the complaints were generated through a Gaussian mixture model on the basis of the boundaries of wards of a generic Tier-2 city in India having a population of around 800,000. These categories included Roads (31%), Sanitation (24%), Water Supply (18%), Electricity (15%), and Others (12%).

Table III: Distribution of Complaint Categories in the Simulation Dataset

Complaint Category	Proportion (%)	Severity Tier	SLA Target
Roads (Potholes, Damage)	31%	Tier 1–2	6–48 hours
Sanitation (Garbage, Sewage)	24%	Tier 3	7 days
Water Supply	18%	Tier 2	48 hours
Electricity	15%	Tier 1–2	6–48 hours
Other	12%	Tier 4	30 days

B. Comparative Evaluation Results

Two baselines were considered to measure system performance; one is the Severity-Only baseline wherein complaints are prioritized according to hazard level alone using the same FIFO strategy. Over the entire 30-day simulation, three measures were tracked:

Table IV: Comparative Evaluation Results

Metric	FIFO Baseline	Severity-Only	UPRA (Proposed)
MTR_1 — Mean Time to Resolution (Tier 1 Critical)	18.4 hrs	6.2 hrs	4.1 hrs
SLA-Breach% at Day 30	38.2%	24.7%	11.3%
Duplicate Record Rate	N/A (all kept)	N/A	34.1% merged
Admin Queue Clarity (qualitative)	Low	Medium	High

C. Discussion

The performance of UPRA is superior in all three metrics compared to either of the two baselines. In addressing the Tier 1 complaints, UPRA is 77.7 percent more efficient than FIFO and 33.9 percent more efficient than the Severity-

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Only order. The comparison of UPRA and the Severity-Only baseline proves the existence of tangible importance of spatial clusters when it comes to prioritizing issues. Unlike the Severity-Only order, where this complaint is viewed as one, and is thus no different from any other complaint, UPRA considers twenty citizens complaining about one issue as one complaint.

The most practically important result from this analysis is the reduction in SLA breach percentages from 38.2% to 11.3% when moving from FIFO to UPRA. It is evident that even low-priority complaints are settled without becoming overdue since the actual Temporal Escalation factor prevents queues from stagnating. Evidence from today's civil platforms that show that a considerable percentage of all complaints registered are duplicates regarding the geographic incident can be attributed to the 34.1% duplication rate.

D. Comparison with State-of-the-Art Systems

UPRA has been compared with three existing systems in Table V for its positioning among the state-of-the-art systems currently available: Vittikh's MCDM based Urban Service Prioritization system [15]; Jan-Samasya portal [12], which is a civic reporting system deployed in Maharashtra; and CivicFix [11], which is a category routing system tested in Indian urban contexts. Six criteria have been considered for the evaluation.

Table V: UPRA's Comparison with State-of-the-Art Civic Complaint Systems

Feature	CivicFix [11]	Jan-Samasya [12]	Vittikh [15]	UPRA (Proposed)
Spatial Deduplication	No	No	Partial	**Yes (Haversine)**
Priority Scoring Model	Category routing only	FIFO + admin override	AHP-based MCDM	**WLC (S + V + T)**
Temporal Escalation	No	No	No	**Yes (SLA-based T factor)**
MTR_1 (Tier 1 Critical)	~12.8 hrs*	~16.1 hrs*	~5.9 hrs*	**4.1 hrs**
SLA Breach Rate	~29%*	~33%*	~18%*	**11.3%**
AI / ML Required	No	No	No	**No**

** Estimated from reported system descriptions in cited works; not directly measured on the same dataset. UPRA figures are measured on the 1,200-record simulation.*

The analysis demonstrates that all three reference systems fail to deal simultaneously with temporal escalation, multicriteria ranking, and spatial deduplication. Thanks to intelligent department routing, CivicFix [11] succeeds over FIFO, but it does not support scoring. Despite the elegant citizen user interface of Jan-Samasya [12], it fails to support deduplication and employs only FIFO as its method of work. The most similar academic precedent is the MCDM framework by Vittikh [15], which utilizes prioritization through the AHP technique. It does not cover deduplication, queue aging fairness, nor supports processing of live citizen requests, which are instead processed offline and curated by experts. To the best knowledge of the authors, UPRA is the first framework to provide a scoring mechanism combining temporal escalation, spatial impact, and severity criteria without resorting to AI.

VII. LIMITATIONS AND FUTURE WORK

However, there are three limitations of the current formula used for calculating UPRA that deserve mention and may point to interesting avenues for future research.

First, instead of using a scientific approach to determining the weights (0.5, 0.3, and 0.2) given to public safety, vehicular transport, and temporal availability respectively, it is assumed that one can rely on intuition and the reasoning that public safety is most important. Using the AHP in well-organised workshops with local government officials, city planners, and community members will likely yield good results in the future.

Second, severity classification currently depends on a fixed lookup table into which citizens manually select a complaint category. Incorporating NLP-based inference that derives severity directly from free-text descriptions would remove this categorisation step, reducing friction for the citizen while improving classification accuracy.

Thirdly, the threshold deduplication distance for all complaint types would be 50 meters. The accuracy of deduplication would be increased across all complaint types if there was a threshold for deduplication that changes based on the category, and the smaller it is for very localized complaints (for example, cracked sidewalks), and the larger it should be for large-scale infrastructural failures, for example, burst water pipes.

There are several other improvements which are planned in the future. The weight of location can be calculated not according to the preset parameter but according to the real-time data on the current traffic density and the number of people on the street. The heatmap can be made available to citizens in order to facilitate transparency and active citizen engagement. Finally, before the launch of the SLA compliance framework during extreme loads, it needs to undergo thorough testing.

VIII. CONCLUSION

UPRA is the name for a well-articulated MCDM technique for civic complaint triaging that was introduced in the current study. It is an illuminating realization, and yet a profound one, that there is much difference in terms of severity and urgency amongst complaints; hence, prioritizing their redress according to a "first-in-first-out" rule results in wastage of public resources, loss of citizenry's trust, and worst of all, overlooks imminent threats to safety.

By integrating Severity, Spatial Impact, and Temporal Escalation under the umbrella of Weighted Linear Combination, while minimizing redundancy in the database using spatial deduplication based on Haversine formula, UPRA turns the otherwise passive complaint repository into a prescriptive analytical instrument that continuously advises administrators about the field locations of their greatest concern.

Important enhancements over the benchmarks are achieved through testing using a carefully designed synthetic test set that produces a 77.7% reduction in the average resolution time of significant complaints, a 70.4% reduction in SLA breaches, and a 34.1% reduction in duplicated records in the database. UPRA does not necessitate AI or any other form of advanced technology; it is relatively simple and straightforward both algorithmically and mathematically, and can be deployed on any standard municipal website. This makes it very effective and quite realistic.

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